Analysis of aerial images to protect marine ecosystems

"Improving Precision & Visualizations"

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ABSTRACT

This project presents a custom-trained YOLOv8 [1] (You Only Look Once) object detection model for detecting boats in satellite images, specifically annotated with data obtained from drone [2] imagery captured by MARRES Master [2] students in the Lérins Islands [3] area. The model, implemented using the Ultralytics library, is trained on a dataset annotated with this drone imagery to enhance its accuracy in local maritime environments. Following training, the model is applied to new aerial images for boat detection, and the detected boat regions are processed to determine their real-world areas. The project integrates morphological [4] operations, visualization of results, and statistical analysis, including counts and categorization of different boat types. Users can manually set thresholds or utilize an automatic approach based on percentiles derived from the boat area distribution. This project serves as a specialized tool for boat detection and analysis in the Lérins Islands [3] area, contributing to applications in maritime surveillance and monitoring.

Figure 1 Lérins Islands area

INTRODUCTION

Welcome to an environmental initiative unfolding in the Iles de Lerins, where the charming landscape faces a significant challenge – the increasing number of boats anchoring in areas rich with Posidonia Oceanica [6], a protected species in the Mediterranean. Despite existing regulations and an eco-mooring park, the pressure on these crucial habitats persists. Stepping up to tackle this issue are dedicated professionals from the Natura 2000 [7] marine protected area, under the supervision of the city of Antibes. Their mission: to devise and implement strategies that bolster mooring regulations, ensuring the preservation of Posidonia Oceanica.

At the heart of this endeavor lies the objective to alleviate mooring pressure on Posidonia Oceanica within the Marine Protected Area, with special attention to Lerins Island due to its heightened susceptibility. The first step involves establishing a comprehensive baseline, encompassing current marine habitat coverage and comprehending boat mooring patterns.

This groundwork sets the stage for MARRES students to propose solutions, including the development of an innovative eco-mooring project. This project is a continuation of the previous semester's initiative, and I have focused on improving measurements and enhancing analysis. Specifically, my research zeroes in on boat detection and classification within the maritime environment of the Lérins Islands. Leveraging advanced AI and machine learning techniques, I aim to address the unique challenges in maritime surveillance, contributing to the ongoing efforts to protect Posidonia Oceanica and its habitat. [8]

Key words: *Iles de Lerins, Posidonia Oceanica, Mooring pressure, Lerins Island, Boat detection, Classification, Machine learning, Maritime surveillance*.

Acknowledgments

I would like to thank Jean Martinet for his supervision of us during this project, and Anne-Laure Simonelli for initiating the project and being our project coordinator. Special thanks to Jean-François Maitre for providing us with the aerial drone picture. My appreciation also goes to Christophe Mocquet and the students of the Master of Science, conservation, valorization of marine resources for providing us information about the Posidonia Oceanica. Finally, I wish to express my thanks to the other members of the Computer Science Master for the participation in the project.

1) State of Art

This project represents a collaborative effort, drawing upon the contributions of previous semester [5]. I have built upon the groundwork laid by my own efforts from the last semester, as well as integrate the work conducted by my colleague Louis Vraie in generating heatmaps.

We continue to advance our efforts in marine ecosystem protection, leveraging cutting-edge object detection techniques, notably YOLOv8 by Ultralytics. This framework excels in real-time object detection, a crucial capability for identifying and categorizing boats within the delicate Posidonia meadows. Building upon the foundation laid in the previous semester's project, we have refined our methodologies to enhance both accuracy and efficiency.

Our dataset is a valuable asset, enriched with aerial imagery obtained from drones, satellites, and photos meticulously captured by MARRES Master students. This diverse collection provides a comprehensive view of Lerins Island and its surrounding areas, facilitating a deeper understanding of the ecosystem dynamics. We have meticulously annotated this dataset, employing tools like Label Studio, to ensure precision in capturing key features.

Additionally, I've sourced a valuable boat database on Kaggle [6], which I plan to utilize to enhance our program's predictive capabilities, specifically in predicting boat models based on their area.

Figure 2 program performance on an aerial drone photo

2) Research and Methodological

Since the beginning of our research, my main focus has been on refining the accuracy of our area measurements. This effort involves two key areas:

firstly, improving the image processing techniques to precisely identify pixels occupied by boats. Through extensive research, I've explored morphology techniques to enhance the precision of this process.

Secondly, I've worked on refining the formula used to convert pixel dimensions to real-world measurements, aiming to improve the accuracy of estimating boat sizes. This required thorough research and reviewing numerous articles to develop a more precise formula, with the goal of aligning the program's calculated area with the actual area of the boats as closely as possible.

Additionally, I found a valuable boat database on Kaggle, providing a wealth of details including boat classes, models, dimensions, weights, and other relevant specifications. Utilizing this dataset, I planned to use the information to predict the boat model identified by the program based on its area, offering additional insights to MARRES Master students.

In terms of analysis, my next step was to create heatmaps for easier interpretation of the program's output. To achieve this, I aimed to advance and simplify the process. Ultimately, I decided to build upon the groundwork laid by our groupmate, Louie, in the previous semester. Leveraging Louie's work, I've developed this aspect of the project, enhancing its complexity and usability.

3) Data preparation

3.1. The source of database

3.1.1. Aerial images

The data for this project was gathered from aerial images to practically address the protection of Lérins Islands [3] marine area. To make the model highly relevant and accurate for the challenges in this locale, I intentionally chose images taken of this geographic region. These images, captured by MARRES Master [2] students in 2021 and 2023 using a drone, cover two key zones:

- Northeastern region of Saint Marguerite.
- Area between the islands.

In this dataset, we have around 150 images, each taken horizontally at a 90-degree angle. These images not only showcase detailed backgrounds but also feature boats of different sizes and types found in the marine environment. By training the model on this diverse dataset, it became adepted at recognizing and responding effectively to the specific characteristics of the local maritime landscape.

Figure 3 Image taken of the area by drone

3.1.2. Kaggel Dataset

Exploring the Kaggle database, Boats_dataset, has granted me access to an extensive array of boat models, complete with detailed specifications like classes, dimensions, weights, and more. With this dataset at hand, my aim is to leverage the information to refine the program's ability to predict the boat model based on its detected area. This predictive enhancement not only bolsters the accuracy of our analysis but also provides valuable insights to fellow MARRES Master students, deepening their comprehension of boat attributes and classifications in marine contexts.

B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
id	type	boatClass	make	model	year	condition	length_ft	beam_ft	dryWeigh	hullMater	fuelType	numEngin	totalHP	maxEngin	minEngin	engineCa
7016498	power	power-center	Glasstrear	240 CCX	2020	new	24	8.25	3300	fiberglass	gasoline	1	200	2020	2020	outboard
5841592	power	power-bay	Glasstrear	228 Bay Tc	2020	new	22.83	8	2300	fiberglass	gasoline	1	200	2020	2020	outboard
4442873	power	power-center	Glasstrear	221 CC	2020	new	22	8.08	NA	composite	gasoline	1	150	2020	2020	outboard
5366255	power	power-center	Glasstrear	221 CC	2020	new	22	8.08	2300	composite	gasoline	1	150	2020	2020	outboard
6834355	power	power-skiwake	Mastercra	Xstar	2019	new	23	8.5	5800	fiberglass	gasoline	1	430	NA	NA	inboard

Figure 4 Kaggel boat dataset

3.2. Data pre-processing

In my efforts to refine the dataset, I carefully scrutinized its contents to identify redundant columns and remove duplicate entries. This process aimed to optimize the dataset's structure for improved efficiency and clarity in subsequent analyses. Additionally, recognizing the significance of accurate boat area representation, I introduced a new column specifically dedicated to this metric. By leveraging the length and width data available in the dataset, I computed the corresponding boat areas in square meters, thus augmenting the dataset with valuable quantitative information. This meticulous refinement procedure ensures that the dataset is tailored to meet the project's objectives, facilitating more precise data analysis and interpretation.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
Unnamed	id	type	boatClass	make	model	length_ft	beam_ft	dryWeigh	hullMater	numEngin	engineCat	length_m	beam_m	Area_m2
1	7016498	power	power-cei	Glasstrear	240 CCX	24	8.25	3300	fiberglass	1	outboard	7.3152	2.5146	18.3948
2	5841592	power	power-ba	Glasstrear	228 Bay Tc	22.83	8	2300	fiberglass	1	outboard	6.958584	2.4384	16.96781
3	4442873	power	power-cei	Glasstrear	221 CC	22	8.08		composite	1	outboard	6.7056	2.462784	16.51444
4	6834355	power	power-ski	Mastercra	Xstar	23	8.5	5800	fiberglass	1	inboard	7.0104	2.5908	18.16254
5	7271315	power	power-po	Starcraft	SLS-1	20	8.5	1921	aluminum	1	outboard-	6.096	2.5908	15.79352
6	7271334	power	power-po	Starcraft	EX 22 FD	22.75	8.5	2100	aluminum	1	outboard-	6.9342	2.5908	17.96513
7	7162591	power	power-otl	Sea Ray	SDX 270 O	27			fiberglass	1	outboard	8.2296	0	0
8	7271322	power	power-po	Starcraft	LX 22 R	22	8	2027	aluminum	1	outboard-	6.7056	2.4384	16.35094
9	7231525	power	power-sal	Scout	235 Dorad	23.67	8.5		composite	1	outboard-	7.214616	2.5908	18.69163
10	7109836	power	power-spi	Scout	355 LXF	35	10.75	9800	fiberglass	3	outboard	10.668	3.2766	34.95477

Figure 5 Kaggel boat dataset after processing

4) Optimizing Area Measurement:

In this project, users have the choice between two methods for determining the boat's area. The first method calculates the real-world area of a bounding box using YOLO coordinates. The second method incorporates YOLO coordinates and morphological operations to estimate the boat's real-world area. By refining the region of interest with morphological processing, this approach ensures accurate pixel-based area calculations and effortless conversion to real-world dimensions.
Our focus will be on improving this second approach.

4.1. Morphological Techniques Enhancement

In the updated version of the script, I have implemented several changes to enhance the accuracy and adaptability of boat pixel extraction.
One of the improvements is the incorporation of dynamic parameter adjustment based on the brightness of the region of interest (ROI). This enhancement allows the script to adapt its morphology parameters to varying lighting conditions, optimizing the extraction of boat pixels across different environments. Depending on the brightness level, the function dynamically adjusts the kernel size and threshold value for morphological operations.
This adaptive approach ensures that the script remains effective in scenarios with different lighting conditions, improving its overall robustness and performance.


Figure 7 boat before adaptive brightness


Figure 6 boat after adaptive brightness

Furthermore, the Morphology function now utilizes the adjusted parameters for morphological operations. Before performing these operations, a Gaussian blur is applied to the grayscale ROI. This step helps in smoothing the image and reducing noise, leading to improved image quality and more accurate pixel extraction.

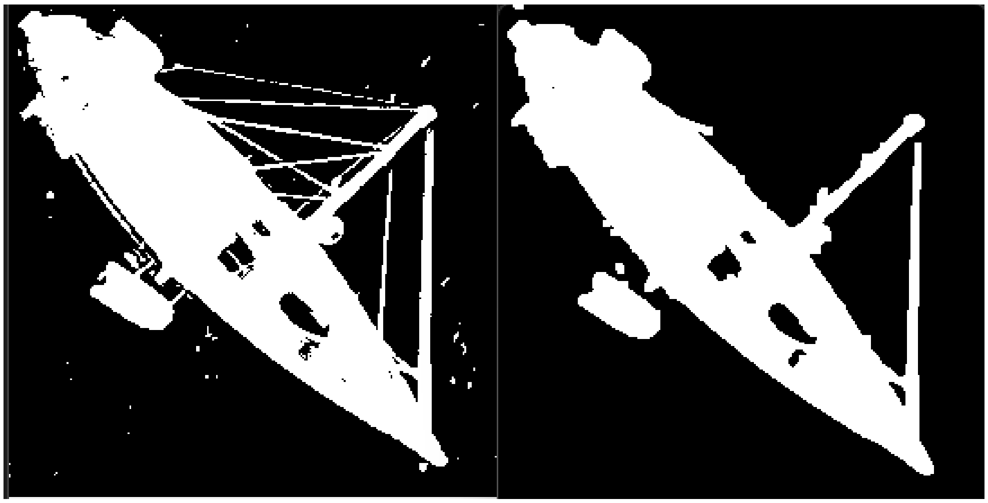

Figure 8 boat before and after removing noise

Overall, the updated script demonstrates enhanced flexibility and adaptability, as well as improved accuracy in boat pixel extraction. By dynamically adjusting morphology parameters based on brightness, the script can effectively handle variations in lighting conditions, making it more robust and reliable for boat detection tasks in real-world scenarios.

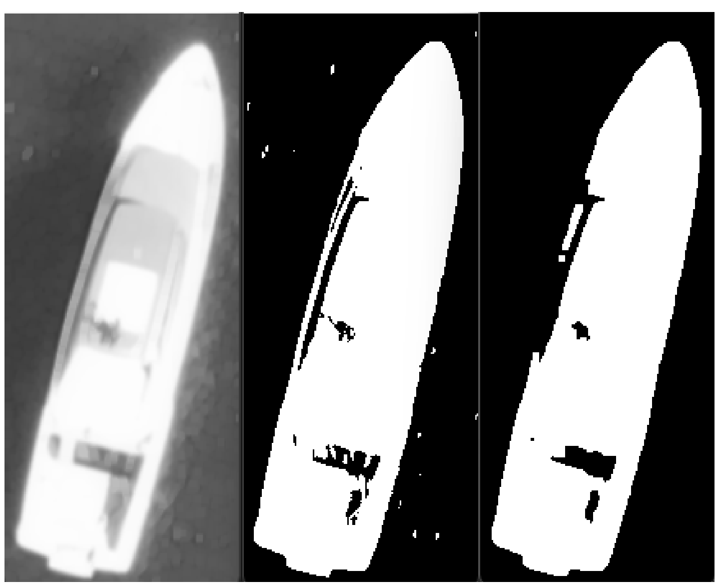

Figure 9 boat before and after morphological optimization

4.2. Pixel Dimension Conversions

After the image processing phase, the program seamlessly connects with the Morphology function, leveraging the processed Region of Interest (ROI). Here, the objective is to determine the object's area in pixels by counting the non-zero pixels within the processed ROI. Following this, we move on to computing Ground Sample Distances (GSD) [8] based on sensor parameters and image size.

Firstly, the calculation of the Ground Sample Distance (GSD) has been streamlined. Instead of computing GSD separately for the X and Y dimensions as in the first version, the new version calculates the average pixel size and utilizes it directly to determine GSD. This simplification enhances code readability and reduces complexity.

Secondly, the method for converting pixel area to real-world area has been revised. In the first version, the conversion involved separately calculating the real width and height of the boat and then multiplying them to obtain the area. However, in the new version, this process has been simplified by directly multiplying the boat's pixel area by the squared GSD value. This approach reduces computational steps and potentially improves efficiency.

```
# Calculating boat area
boat_area_pixel = np.count_nonzero(res)

Pixel_Size_X=sensor_size[0]/imgsize[0]
Pixel_Size_Y=sensor_size[1]/imgsize[1]
Average_Pixel_Size=(Pixel_Size_X+Pixel_Size_Y)/2

gsd = Average_Pixel_Size * altitude / focal_length

# Convert pixel coordinates to real-world coordinates
eara = boat_area_pixel * (gsd ** 2)
```

Figure 10 pixel dimension conversions

5) Model Recommendation System

I've developed a function to recommend boat models based on their respective areas, with the aim of offering additional insights to MARRES Master students. This function processes boat dataset information extracted from CSV files: "Boats_With_Area_mm2.csv," which contains various details about different boat models, and "boats.csv," which lists the detected boats and their calculated aera in a given image. By leveraging this function, MARRES Master students can gain valuable insights into boat model recommendations, enhancing their understanding of maritime resources and technologies.

This function goes through each detected boat, considering a ±2% error margin for the boat's area to determine similar models. Recommendations are then made, including boat IDs, models, areas, and suggested models with their areas. These recommendations are shown to the user for review and saved to a CSV file for later use. The script manages the main process, setting up boat data and running the recommendation function based on user input.

```
Detected boats:
          model  Area_m2
1   Mootor boat       76
2   Mootor boat       74
3   Mootor boat       69
4   Mootor boat      114
5   Mootor boat       46
6   Mootor boat       30
7   Mootor boat      315
8   Mootor boat       51
9   Moving boat       55
10  Mootor boat       16
11  Mootor boat       33
12  Moving boat       35

Recomended boats?(Y/N) y
* Boat number: 1 | Type: Mootor boat | Area: 76.68298165012935
Possible Models:
Hudson Bay 50 Sedan (power) - Area: 75.30 mm^2
C52 Command Bridge (power) - Area: 75.70 mm^2
48 Open (power) - Area: 75.81 mm^2
48 Sport Coupe (power) - Area: 75.81 mm^2

* Boat number: 2 | Type: Mootor boat | Area: 74.5324761724052
Possible Models:
Hudson Bay 50 Sedan (power) - Area: 75.30 mm^2
C52 Command Bridge (power) - Area: 75.70 mm^2
48 Open (power) - Area: 75.81 mm^2
48 Sport Coupe (power) - Area: 75.81 mm^2
Oceanis 51.1 (sail) - Area: 74.62 mm^2
```

Figure 14 recommended boats

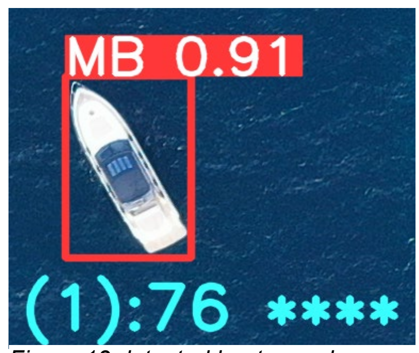

Figure 13 detected boats number one

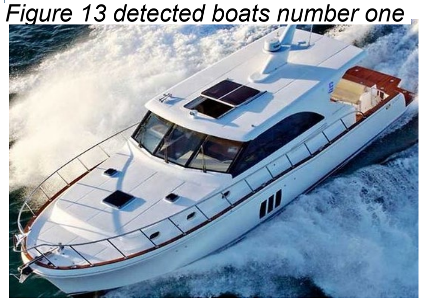

Figure 11 recommend boat model 50 Sedan

Figure 12 recommend boat model 48 Open

6) Heatmap

In my project to improve our app's efficiency, I added a heatmap feature. My colleague Louis had worked on this last semester, focusing on how boats are spread out. I took his work and made some changes to combine it with my own code. The goal was to give the MARRES Master project more detailed info and analysis.

First, I looked at what Louis had done before. His work was split into two parts: finding boats and training a model. Since we didn't need to train a new model, I just tweaked the boat detection part, which created a CSV file with boat locations.

I added more details to this file from my own code, which figures out how big each boat is. This combined data was then used to make the heatmap.

By bringing together our work, I made a heatmap that not only shows where boats are at different times but also lets users filter by boat size. For example, they can see where the big boats are anchored.

This info will be helpful for the MARRES Master project to make better decisions about maritime activities.

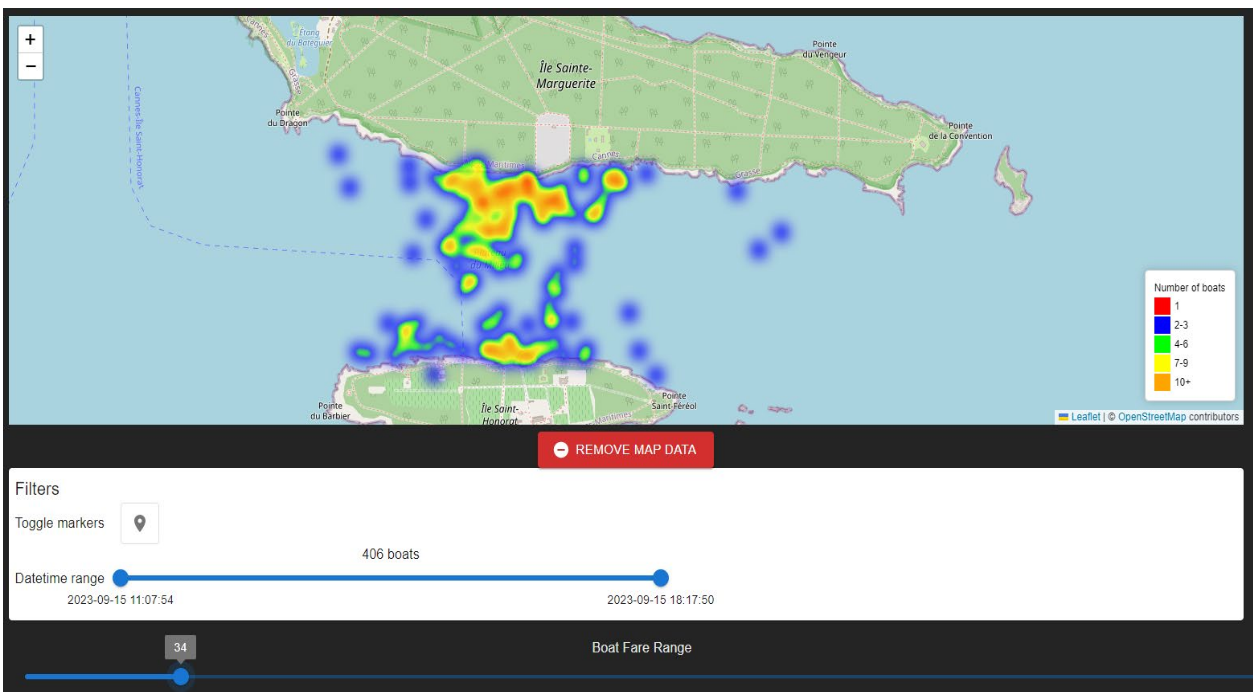

Figure 15 Heatmap

7) User interface:

In the script, users will be asked to make decisions about how to calculate the area and set thresholds for classification.
They'll also be able to adjust class intervals.
These choices include:

7.1. Area calculation

The user is prompted to choose between two methods for area calculation: Pixel base or Bounding box base.

1. If the user chooses pixels, the code calculates the area using Area_pixels().
2. If the user chooses boxes, the code calculates the area using Area_boxes().

7.2. Setting class intervals

7.2.1. Based on the collective area of all boats in the database

If the user selects this option, the program asks whether the user is working with a new dataset.

If it's a new dataset, the script imports Results_and_Statistics.py to utilize the General_thresholds function for reading class intervals from 'class_intervals.txt'.
If it's not a new dataset, the script continues without importing Results_and_Statistics.py and directly reads the class intervals from the 'class_intervals.txt' file.

7.2.2. Based on the range of boat areas present in the selected image

If the user selects this option, the script calls the Set_thresholds function. The Set_thresholds function automatically determines class intervals and thresholds based on the distribution of boat areas calculated from the current input. This option is suitable when the user wants to adapt the classification thresholds to the specific characteristics of the current image.

Saving and reusing classification thresholds in the 'class_intervals.txt' file makes the boat detection and classification process smoother. This method improves the ability to reproduce and adjust the system, so users can easily switch between different datasets while keeping the size categories consistent. By offering a simple option to create new intervals or use existing ones, the script allows for flexibility in analyzing various maritime images, making the analysis pipeline stronger and more adaptable.

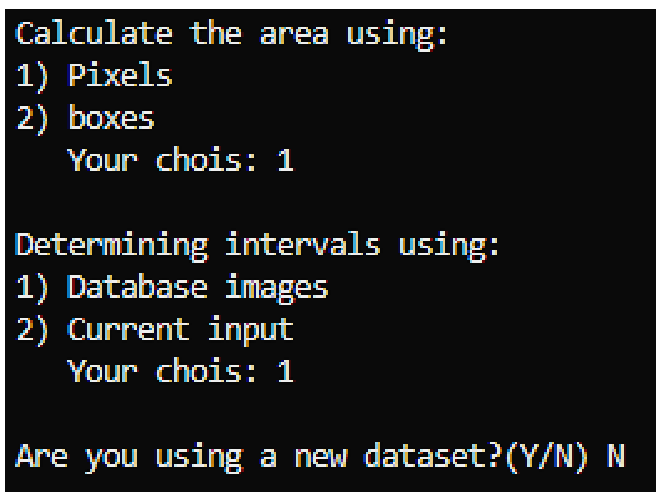

Figure 16 user interface

At the end, the program will ask the user if he wants to see the proposed models or not and will move forward based on the user's choice.

8) Accuracy evaluation

To gauge the accuracy of my program's area calculations, I adopted an innovative technique suggested by Professor Martinet. Using a drone positioned at heights of 10, 20, 30, and 40 meters, I used a recorded footage of a piece of A4 paper with a known area. Afterward, I extracted different frames from the video at each height and used the Roboflow website to pinpoint the object's location within each frame. With morphological component analysis, I isolated the pixels corresponding to the paper in the images. By feeding the pixel count, camera specs, and photo metadata into my area calculation function, I estimated the A4 paper's area.

My program determined the paper's area to be 645 square centimeters, exhibiting a 3.6% deviation from the standard A4 size of approximately 623 square centimeters. I used this error percentage as a reference for assessing the acceptability of deviations in proposed boat model measurements, as discussed previously.

This methodology offers a systematic and data-driven approach to evaluating measurement accuracy, with potential applications beyond the scope of this study.

Figure 17 image taken at a height of 10m

Figure 19 image taken at a height of 20m

```
calculated area:  645 cm²
Real area:  623 cm²
Absolute Error: 22.87555685161078 cm²
Relative Error: 3.671838980996915 %
```

Figure 18 Calculated error percentage

9) Results and discussions

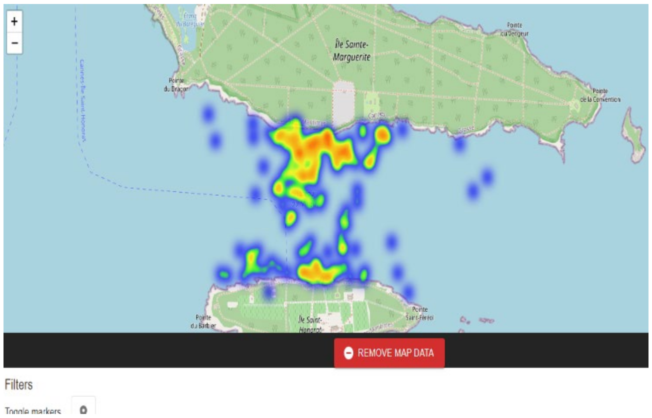

Figure 22 heatmap of boats between 0 and 34 m²

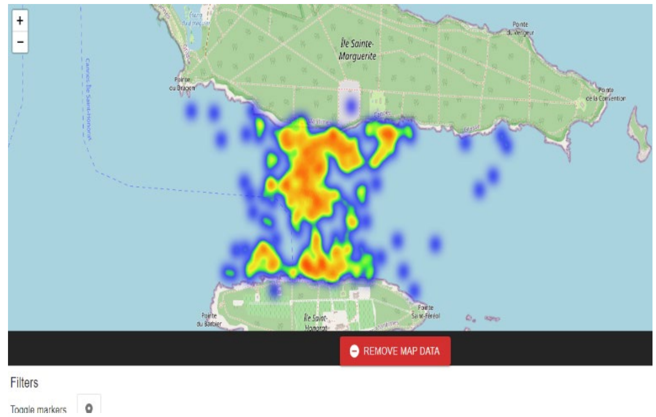

Figure 23 heatmap of boats between 34 and 53 m²

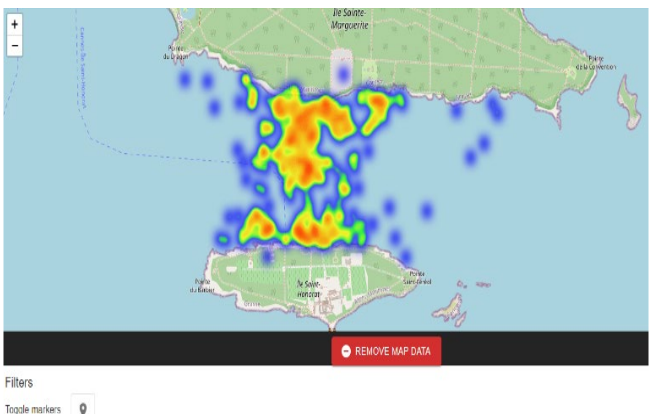

Figure 20 heatmap of boats between 53 and 74 m²

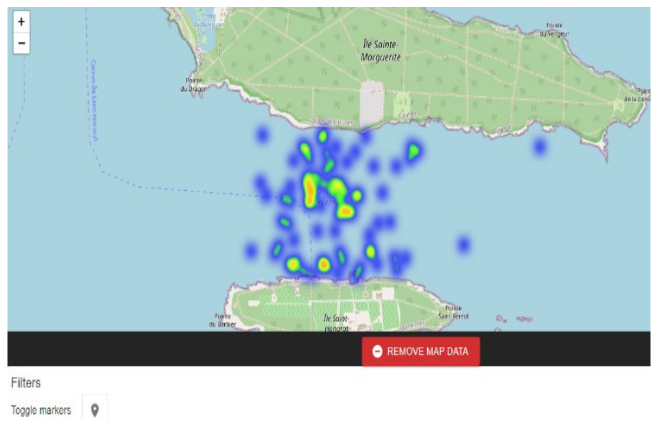

Figure 21 heatmap of boats bigger than 74 m²

The distribution of boats within the Marine Protected Area offers valuable insights into the ecological dynamics of the region. The correlation between boat size and anchor size highlights the potential stressors on the marine environment, particularly concerning the integrity of the posidonia oceanica seagrass beds. These seagrass meadows play a crucial role in maintaining water quality, providing habitat for marine life, and stabilizing coastal sediments. Therefore, pinpointing areas devoid of posidonia oceanica is essential for identifying zones where large boats may exert undue pressure on fragile ecosystems. This information can inform targeted conservation efforts and regulatory measures to mitigate the impact of vessel anchoring activities on marine biodiversity and ecosystem resilience within the Marine Protected Area.

10) Challenges

In the course of executing the project, I encountered multifaceted challenges that extended beyond technical intricacies, encompassing issues related to hardware limitations and the meticulous process of data annotation. Attempting to train the model on a local machine brought to light the delicate balance required between computational constraints and achieving optimal model performance.

To address hardware limitations, I engaged in extensive experimentation, seeking configurations that would reconcile the constraints of the local setup with the need for accurate model training. This iterative process not only honed my troubleshooting skills but also deepened my understanding of navigating challenges in resource-constrained environments.

Additionally, determining the real-world size of boats introduced another layer of complexity to the project. This task required the integration of diverse variables and mathematical equations to precisely calibrate the model's understanding of object dimensions in the physical world. Tackling this challenge deepened my awareness of the interdisciplinary nature of computer vision projects, where technical skills intertwine with domain-specific knowledge.

In summary, the project journey not only involved technical problem-solving but also spanned a broader range of skills, from optimizing hardware to meticulous data preparation and domain-specific considerations. The iterative process of overcoming these challenges significantly contributed to my ongoing learning and growth as a practitioner in the field of computer vision.

11) Conclusion

In bringing the boat detection and classification project in the Posidonia marine environment to its conclusion, the project has delivered promising results with practical implications for both marine students and environmental surveillance. The detailed classification of boats, coupled with the recognition of motion statuses, provides a comprehensive overview of boat activity in the region. As the project moves forward, addressing identified limitations and incorporating feedback from MARRES [2] students and environmental experts will contribute to its continual refinement and application in real-world scenarios. Overall, the project represents a successful intersection of technology, education, and environmental monitoring, paving the way for informed decision-making and sustainable marine conservation efforts.

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